RISK OF JOB AUTOMATION AND PARTICIPATION IN ADULT EDUCATION AND TRAINING: DO WELFARE REGIMES MATTER?

ABSTRACT

This study explores the relation between risk of job automation and participation in adult education and training (AET) and examines variation in that relation across welfare regimes distinguishing between situational and institutional barriers. Using microdata of PIAAC we analyse participation in formal or non-formal AET for job-related reasons in relation to the risk of automation of the respondents' occupation after controlling for main socio-demographic characteristics. Logistic regression models are run on respondents from fourteen European countries representing different welfare regimes: Denmark, Norway and Sweden (Scandinavian countries); Italy, Greece and Spain (Southern European); Czech Republic, Slovakia and Poland (Central and Eastern Europe), Belgium, France and Germany (Continental) and UK and Ireland (Anglo-Saxon countries). Our findings confirm that workers in occupations at high-risk of automation were found to be consistently less likely to participate in job-related AET, quite irrespective of welfare regime.

Keywords: job automation, participation in adult education and training, Matthew effects, unmet demand, barriers in participation in adult education and training, cross national comparison.

1 INTRODUCTION

The effects of automation technology on the labour market are one of the most pressing questions of our time. On the one hand, estimates of the number of jobs at risk of becoming obsolete as automation technology advances vary widely (Arntz, Gregory, & Zierahn, 2016; Brynjolfsson & McAfee, 2014; Frey & Osborne, 2013; Josten & Lordan, 2019; Nedelkoska & Quintini, 2018). On the other hand, uncertainty lingers about the net effect of automation technology on employment, i.e. about the relative size of displacement effects of automation (job destruction) vs. reinstatement effects (job creation) (Acemoglu &

Restrepo, 2019; Autor, 2019; Bessen, Goos, Salomons, & van den Berge, 2019). Nevertheless, even under the most optimistic scenario, dislocations are likely to be substantial: the new jobs are likely to be distant in time as well as space, and to be in different firms and industries from the jobs made obsolete by technology.

One relevant dimension for public policies to deal with these challenges is 'reskilling'. An obvious problem with such a public policy response is that it will require a level of financial resources and political commitment that are not always evident. A less obvious problem is inequality of access to adult education and training (AET) for disadvantaged groups. Previous research has established that the highly educated are more likely to participate in AET and has highlighted various aspects of the so-called Matthew effect, meaning that initial educational inequalities perpetuate over the life (Blossfeld, Kilpi-Jakonen, Vono de Vilhena, & Buchholz, 2020; Boeren, 2009; Lee & Desjardins, 2019). This effect is often referred to as the cumulative advantage/disadvantage hypothesis (O'Rand & Henretta, 1999).

Matthew effects are less well studied in relation to the risk of automation. Workers in fully automatable jobs were found to be four times less likely to have participated in job-related training than workers in non-automatable jobs (Nedelkoska & Quintini, 2018). Also, workers whose jobs are at high risk of automation were found to be 30 percentage points less likely to engage in adult learning than their peers in less exposed jobs (OECD, 2019).

The paper builds on two strands of existing literature. The first deals with skill biased technological change and attempts to estimate the risk of automation of a job (Arntz et al., 2016; Frey & Osborne, 2013; Josten & Lordan, 2019; McGuinness, Pouliakas, & Redmond, 2019; Nedelkoska & Quintini, 2018). The second addresses AET participation as a result of structural conditions and individual agency and distinguishes between demand and supply barriers to participate (Boeren & Holford, 2016; Hovdhaugen & Opheim, 2018; Roosmaa & Saar, 2016; Rubenson & Desjardins, 2009). The type of welfare regime can influence both structure and agency (bounded agency model according to Rubenson & Desjardins, 2009).

Our analysis explores if the negative relation between risk of automation and probability of participation in AET is equally robust across welfare regimes. Moreover, it investigates how different types of barriers affect AET participation and whether said patterns vary by welfare regimes and by risk of automation.

2 PARTICIPATION IN ADULT EDUCATION AND TRAINING AND RISK OF JOB AUTOMATION

2.1 Explaining adult learning participation

There is a vast amount of literature - both theoretical frameworks and empirical studies – attempting to model and explain why adults participate in education and training (for a systematic review and discussion see Boeren, Nicaise, & Baert, 2010). Scholarship in this field focuses either (a) on individual determinants or (b) on system-level characteristics or (c) on the interaction between different levels (micro-, meso- and macro-level) that shape participation in adult learning.

Theoretical models focusing on *individual determinants* for participating in AET involve approaches from psychology, sociology, and economics. The most influential among them is the Human Capital Theory (Becker, 1993) arguing that decisions to participate in AET are rational based on cost-benefits calculations. Motivational theories (Cross, 1981; Eccles & Wigfield, 2002) highlight the role of motivation and beliefs for participating in learning activities, other theoretical frameworks focus on attitudes and subjective norms towards certain behavior patterns (Ajzen & Fishbein, 1980). Other models inspired from comparative political economy and welfare state research highlight the importance of institutional and public policy frameworks (Blossfeld et al., 2020; Desjardins, 2017; Saar, Ure, & Desjardins, 2013). These macro-level determinants are considered to influence both supply and demand for participation in AET. The most common assumption for explaining participation in AET, though, is the interaction between different levels (micro, meso, macro) (Boeren 2016) or the interplay of structure and agency (Desjardins & Rubenson, 2013). *Structure* refers to supply, in terms of institutional provision for AET (meso-level) as well as to opportunity structures for adult education influenced by legal and financial regulations of AET, but also by labour market, economic and political institutions (macro-level). *Agency* refers to the demand for AET (operationalized as the individual resp. micro-level), which is influenced by characteristics of the meso- and macro-level, but also by individual and job-related characteristics. Rubenson and Desjardins (2009) adopted the welfare state regimes framework to analyse the state´s role in shaping the broader structural conditions that are relevant for participation in adult education. According to them, the type of welfare state regime shapes the broad structural conditions, which in turn bind or constrain individuals´ capabilities and choices (bounded agency model). Previous research on the relevance of country groupings in relation to participation in adult education and in-company training has demonstrated strong overlaps with existing welfare state typologies (Desjardins & Rubenson 2013; Saar, Ure, & Desjardins, 2013; Markowitsch, Käpplinger & Hefler 2013). While individual determinants of participation are rather similar across countries with educational attainment, employment status, occupation and age having a high predictive power, country-specific structural conditions seem to play a significant role in the provision and take up of learning opportunities. Research has shown that participation rates in Scandinavian countries are much higher than those in Southern and Eastern European countries and that inequalities between different socio-economic and occupational groups tend to be smaller in these countries. Scandinavian countries are known to have inclusive adult learning systems and to support overall participation with generous benefits systems and a range of targeted social policy measures (subsidies, family care, education leave) (Saar, Ure, & Desjardins, 2013; Desjardins, 2017). These findings demonstrate that participation in AET is more than an individual choice; it takes place in interaction with broader structural conditions and can, thus, be partially explained by the country and its welfare regime type. Countries with an extended welfare state tend to invest more in mitigating inequalities by spending more in interventions in education and active labour market policies and by extending support to low-skilled adults, those at risk of exclusion or disruption. Workers in occupations at high risk of automation are more likely to benefit from this type of interventions.

Another literature strand deals with the reasons for non-participation in AET focusing explicitly on barriers. The most frequently cited theoretical framework developed by Cross (1981) distinguishes between situational, dispositional and institutional barriers to participation in AET. *Situational* barriers are related to a person's life situation at a given point in the family life cycle and working life. *Dispositional* barriers refer to personality traits or personal qualities acquired through early school experiences. *Institutional barriers* include institutional practices and procedures that discourage or prevent participation. Research has shown that there are country specific institutional arrangements that determine the levels of barriers and enable individuals to overcome them (Cabus, Ilieva-Trichkova, & Štefánik, 2020; Hovdhaugen & Opheim, 2018; Roosmaa & Saar, 2016).

2.2 Participation in AET and risk of job automation

For obtaining a systematic literature review on the relationship between risk of job automation and participation in AET we searched (in May-June 2020 period) through the following databases: ERIC, Fachportal Pädagogik, Google Scholar, Springer Link, Researchgate, Sage Journals, Google Scholar, BIBB, ECONBIZ, GESIS, OECD library, BASE.

We used the keywords “risk of job automation” AND (participation in) “training”/ “reskilling”/ “adult learning”/ “further education”/ “continuing education”. We applied a staged review, which led us to 485 matches, of which 104 were included in the initial review. Table I in the online appendix provides an overview of the search strategy.

Inclusion criteria: English and German language, theoretical and empirical studies published between 2001–2020, grey literature (policy reports and working papers) was considered, if publicly accessible.

Exclusion criteria: papers stating only one of the key words (only participation in AET or only risk of job automation) and not (different) combinations of them, papers focusing only on the vocational education and training system.

A final list of 25 studies has been in depth-reviewed (see Table II in the online appendix).

All 25 studies use quantitative data; only one uses qualitative data. The majority are working research papers published by international organisations (OECD) or national research centres. There are some reports by private organisations, the EU and the World Bank. Most studies work with OECD databases (PIAAC dataset is one of the key sources), European and national data from labour force, social service and household surveys. Countries covered are OECD and EU countries, frequently with a regional or national focus.

All studies stress that technology will fundamentally change work; the majority addresses the labour market implications of technological changes, automation and digitalisation, a couple of them also address the macroeconomic implications. Estimations on jobs at risk due to digitalisation and technological change differ significantly dependent on the method used to calculate the risk of job automation. The reviewed studies use either the occupation based approach by Frey and Osborne (2013) or the task based approach by Arntz et al. (2016). The occupation-based approach obviously displays more jobs at high risk of replacement than the task-based approach (e.g. in Italy 33.2% vs 18.1% according to Filippi & Trento, 2019) as the latter assumes that many seemingly automatable occupations often contain a substantial share of tasks that are hard to automate (Arntz, Gregory, & Zierahn, 2019).

Despite significant variation in the findings regarding the calculated risk of job automation, all studies conclude that low-skilled, less-educated workers, young people, and men are most likely to experience disruption and displacement by technological change and point to implications for skills demand and skills supply. In addition, some studies consider employment, social, and education and training policies to facilitate adaptation to these challenges.

None of the reviewed studies examines the relationship between risk of job automation and participation in AET, except one by Nedelkoska and Quintini (2018) on the risk of automation and its interaction with training incidence and the use of skills at work. Pouliakas (2018) explores the determinants of automation risk in the EU labour market focusing on the relationship between jobs with high risk of automation and (low) demand for skills among EU employees.

3 RESEARCH QUESTIONS AND METHODOLOGY

Having outlined the main theoretical perspectives and reviewed the literature, we now address our research questions empirically:

i. Is the negative relation between risk of automation and probability of participation in AET equally robust across welfare regimes?
ii. Do the relevant patterns concerning barriers vary by risk of automation and by welfare regimes?
iii. Does the risk of automation exert an independent effect on the probability to participate in AET, and on unmet demand for AET, once controlling for other relevant factors?

3.1 Data

The Survey on Adult Skills of the Programme for the International Assessment of Adult Competencies (PIAAC) is used for the analysis. PIAAC gathered data on a range of education and training activities undertaken by adults aged 16 to 65 in the 12 months preceding the interview including formal education programmes and non-formal learning activities.

For the purposes of this analysis, we selected fourteen European countries and grouped them in five welfare regimes taking in consideration data availability in the public files (e.g., ISCO-2digits). These are the original 'three worlds of welfare capitalism' (Esping-Andersen, 1990):

- Scandinavian social democratic (Sweden, Norway and Denmark),
- liberal Anglo-Saxon (UK and Ireland), and
- conservative Continental European (Germany, France and Belgium),

plus, two welfare regimes proposed in later work:

- Southern European (Italy, Spain and Greece), as discussed by, among others, Ferrera (1996),
- Central and Eastern European, in particular its 'embedded liberal' cluster (Poland, Czech Republic and Slovakia), identified by Bohle and Greskovits (2012).

3.2 Methodological choices

3.2.1 Dependent variables

i) Participation in formal or non-formal AET for job-related reasons in 12 months preceding survey.

ii) Unmet demand for AET.

We focus on AET for job related reasons because evidence on cross-national participation patterns shows that the majority of organized AET is undertaken for job related reasons, is employer-sponsored and non-formal opportunities make up a significant proportion (Desjardins, 2017, pp. 188–189).

In line with the literature (Hovdhaugen & Opheim, 2018; Roosmaa & Saar, 2016; Rubenson & Desjardins, 2009), we define unmet demand for AET as training or education for career or job wanted but not taken in the last 12 months. This category includes both those who did not take any AET activities in the previous year and those who took part to some training but are asking for more. As for the reference category, we separate those who don't report unmet needs and have not undertaken any AET activities in the previous year from those who don't report unmet needs but have participated in AET in the last 12 months. Drawing on the work of Rubenson and Desjardins (2009) and Roosmaa & Saar (2016) on reasons for unmet demand for AET, we distinguish between situational and institutional barriers as follows:

- Situational barriers: lack of employer's support; too busy at work; did not have time because of childcare and family responsibilities.
- Institutional barriers: did not have the prerequisites; education or training too expensive/ could not afford it; course or programme offered at an inconvenient time or place.

We do not examine dispositional barriers, referring to personality traits as those appear to be more manifest to persons who are not interested in participating in AET (Roosmaa & Saar, 2016; Rubenson & Desjardins, 2009), and thus, more likely to be found in the group "no demand" (Hovdhaugen & Opheim, 2018, p. 562).

3.2.2 Defining the risk of automation

We assign for each observation the average risk of automation figure per occupation (ISCO[1] code) per country estimated by Nedelkoska and Quintini (2018), as published in the online appendix. Nedelkoska and Quintini (2018) estimated the risk of automation at individual level. Our variable provides a rougher approximation, as it disregards variation within occupations. Naturally, our figures closely match the mean and median risk of automation per country estimated by Nedelkoska and Quintini (2018).

3.2.3 The regression analysis

We estimate odds of participation in AET and having unmet training needs using logistic regression models. Specifically, we estimate the independent effect of risk of automation by occupation on the probability to participate in (job-related) AET, and on unmet demand for AET, over and above the well-established effect of other variables, included as controls.

The independent and control variables used in the regression models are the following:

Independent variable

- Risk of automation by occupation (two-digit ISCO code[2]), in classes of 10 percentage points; values below 20% and over 70% grouped together (fewer observations at two extremes).

Control variables

- Gender, as women on average are less active in the labour market and more likely to face situational barriers to participation due to the unbalanced division of responsibilities within households (Massing & Gauly, 2017);

[1] ISCO: International Standard Classification for Occupations

[2] ISCO of previous job was used for those not working at the time of the interview.

- Age, as disparities in participation of older people in AET have been highlighted (Philipps, 2020);
- Education (low: ISCED[3] 0-2, medium: ISCED 3-4, high: ISCED 5-8), which could be used as an indicator of skills levels (Mayer & Solga, 2008; Tikkanen & Nissinen, 2018);
- Employment status (employee, self-employed or not working, the latter excluding retirees); employees are further analysed into standard (permanent = indefinite contract *and* full-time = working >=30 hours a week) and non-standard (temporary = fixed-term contract *and/or* part-time = working <30 hours a week), as part-time and temporary jobs are associated with less labour market attachment, thus, less training opportunities and less expected outcomes from investment in training. This is valid for both the workers' and the employers' point of view (Arulampalam & Booth, 1998);
- Welfare regime (Scandinavian, Southern, Continental, Central-Eastern, Anglo-Saxon), as particular welfare regimes seem to shape favourable structural conditions which enable disadvantaged groups to overcome barriers and participate in learning opportunities (Rubenson & Desjardins, 2009).

We run logistic regressions on each dependent variable, first pooling data for all fourteen countries, then for each of the five welfare regimes separately. This is the approach recommended by Bryan and Jenkins (2015), when the main interest is in the effects of individual regressors' rather than in country-level predictors.

From the reference population persons aged 16-24 are excluded (as most of them are still in formal education attainment) and so are those who are retired or in early-retirement (as our main interest is job related AET). We only focused on individuals who have not changed firm or organization in the last 5 years

[3] ISCED: International Standard Classification of Education

(36,118 individuals[4] out of 57,640) to avoid to potentially capture those who moved from occupations under high risk of automation to jobs in new workplaces with fewer risks (which are the current ones reported in the survey) as a result of recent training[5].

Data is weighted using weights provided by PIAAC dataset.

4. RESULTS

4.1.1 Descriptive analysis

The descriptive analysis provides answers to our first two research questions.

4.1.2 Risk of automation by welfare regime

A job is considered to be at risk of automation if it has a 50% or higher probability of being automated (OECD, 2019, p. 38). As seen in Table 1, average risk of automation (across workers in all occupations) varies between welfare regimes, from around 42% (Scandinavian and Anglo-Saxon) to around 50% (Southern, Continental and Central-Eastern). Over 80% of jobs in Scandinavia (Sweden, Norway and Denmark) were in occupations at low average risk of automation (probability <50%).

Insert table 1 here

[4] Variables used in the analysis are not subject to major missing data issues. The number of cases missing is less than 1% except for the variable related to occupational status (2,421 cases or 6.7% missing).

[5] Data available don't allow us to identify individuals who changed jobs within the same organization. Therefore, we are not able to exclude from the analysis individuals who moved from high to low risk of autonomation jobs with the same employers as a result of recent AET training.

As explained in the previous section, averages tend to conceal variability: Nedelkoska and Quintini (2018) estimated that the share of individual jobs at low risk of automation (defined as having less than 30% chance of being automated) in Scandinavia varies from 61.7% (Denmark) to 68.6% (Norway). Clearly, variation is big not only within welfare regimes but also *within* the same country and across regions. For instance, in the countries for which data is available, the share of workers in jobs with a risk of automation equal to or larger than 50% sometimes can vary more than two-fold across regions (OECD, 2019, p. 39).

4.1.3 AET participation by risk of automation

Our first question asks whether the negative relation between risk of automation and probability of participation in job-related AET found in the literature (Nedelkoska & Quintini, 2018; OECD, 2019) is equally robust across welfare regimes. Table 2 provides an answer to that question. Overall, the rate of participation in job-related AET is highest in Scandinavia (55%), closely followed by Anglo-Saxon countries (50%), and lowest in Southern Europe (29.5%), with continental (42%) and Central-Eastern European (34.0%) countries located somewhere between the two extremes. This is in line with cross-national empirical evidence on overall participation rates (Roosmaa & Saar, 2010; Rubenson & Desjardins, 2009). However, across all welfare regimes, participation in job-related AET tends to fall as the risk of automation increases.

In line with the literature (Blossfeld et al., 2020; Lee, 2018), we expected that the type of welfare state regime might have an impact on both the overall participation rate in AET and on its unequal distribution. The picture appears to differ slightly by welfare regime. The average participation in job-related AET in Scandinavia is 1.5 higher in occupations at low risk of automation relative to those at high risk. That differential, though rather high, is actually lower than in all other welfare regimes (ranging from 1.61 in Anglo-Saxon to 2 in Central-Eastern European countries).

Insert table 2 here

4.1.4 Unmet demand for AET by risk of automation and welfare regimes

Our second question refers to demand for and barriers to participation in AET by risk of automation and by welfare regime. We focus on unmet demand for AET defined as training or education for career or job wanted but not taken in last 12 months. One might have thought that AET participation and unmet demand for AET are negatively correlated. As shown in Table 3, this hypothesis is not confirmed. Moreover, unmet demand is lower among workers in high risk of automation: not only are workers in jobs at higher risk of automation less likely to participate in AET, but also less likely to be aware of their training needs.

Insert table 3 here

The relevant patterns differ across welfare regimes. In the high-participation regimes (Scandinavian and Anglo-Saxon), two different situations emerge: in Scandinavian countries, the share of respondents expressing unmet demand is highest, while in Anglo-Saxon countries the quota of workers with unmet needs is average and show similar values of Continental and Southern countries. What they have in common is that both welfare regimes show the lowest low to high ratio related to unmet demand (around 1.35), meaning the share of workers expressing unmet demand is most similar between workers at different risks of automation. In contrast, in Central-Eastern European countries, where participation in job-related AET is among the lowest (34.0%), respondents who wanted but did not take job-related training over the previous year were twice as high among workers at low risk of automation.

4.1.5 Barriers to AET participation

Our second research question additionally asks whether the pattern of barriers to participation in AET across welfare regimes varies by risk of automation.

Table 4 presents the ratio between the quota of individuals declaring a situational barrier divided by the quota of those selecting an institutional barrier.

The findings show that situational barriers outweigh institutional ones across all welfare regimes. The relation between barriers of one kind or the other is most balanced in Central-Eastern Europe followed by Anglo-Saxon countries (only for low-risk occupations), and most unbalanced in Southern Europe.

Insert table 4 here

As shown by values higher than one, the predominance of situational over institutional barriers holds across classes of risk of automation in all welfare regimes. Interestingly, as shown by values of the low-to-high ratio[6] closer to one, the barriers and constraints facing workers in jobs at high risk of automation seem to be more evenly balanced in Southern and Central-Eastern welfare regimes. Anglo-Saxon countries are the only group where the gap between situational and institutional barriers is higher among workers at low risk of automation. Situational barriers have similar effects on workers there regardless of the risk of automation of their jobs (12.4% vs 10.2%) while institutional barriers are more perceived among workers at low risk of automation (7.4% vs 4.3%).

4.1.6 Inferential analysis

Our third and final research question asks whether the risk of automation exerts an independent effect on the probability to participate in AET, and on unmet demand for AET, over and above the effect of controls such as education, gender, age, employment status. Moreover, we check if such effect is consistent among welfare regimes.

Figure 1 displays the probability of participation in job-related AET as estimated by our logistic regressions.

Once controlling for the other factors included in the model, men (gender differences are the least steep), young people and higher-educated workers are more likely to participate in job-related AET than women, older people and lower-educated workers. The same is true for employees over the self-employed or those out of work. Confirming the results of the descriptive analysis, individuals from Scandinavian and Anglo-Saxon countries are more likely to participate in job related AET while persons from Southern and Central-Eastern Europe countries show the lowest probabilities. Therefore, the different participation rates are not due to impacts of the composition of the workforce. However, even when all these factors are controlled for, the probability to participate in job-related AET remains significantly (and negatively) associated with risk of automation.

Figure 1. Conditional probabilities estimated from logistic regression on probability of AET. Confidence intervals at 95% level of statistical significance.

Focusing on the outcomes by welfare regimes, it is noticeable that, while low levels in the risk of automation are associated with higher predicted probabilities in AET participation in all welfare regimes (figure 2), in Central-Eastern and Anglo-Saxon countries the gap between the estimated probabilities of AET participation of low and high-risk workers appears to be slightly higher, while in Southern countries the differences are the smallest (as shown by the flattening trend of the curve in figure 2).

Figure 2. Conditional probabilities of AET by risk of automation. Regressions separately run by welfare regimes. Confidence intervals at 95% level of statistical significance.

Age seems to play a greater role in determining who participates in job-related AET (and who does not) in Scandinavian and Continental countries than in other welfare regimes (figure 3). In these two welfare regimes, the probabilities to participate in AET is significantly lower (compared to other age groups) for workers aged over 55 years old.

Figure 3. Conditional probabilities of AET by age. Regressions separately run by welfare regimes. Confidence intervals at 95% level of statistical significance.

Non-standard (temporary and/or part-time) employees are significantly less likely to participate in job-related AET relative to standard (permanent and full-time) employees, though more likely than self-employed and non-working respondents, a pattern that holds consistently across all welfare regimes (figure 4).

Figure 4. Conditional probabilities of AET by employment status. Regressions separately run by welfare regimes. Confidence intervals at 95% level of statistical significance.

While low educated workers are less likely to participate in job-related AET in all welfare regimes, the raise of the line is less steep in Scandinavian and Anglo-Saxon countries than it is elsewhere (figure 5). On the other hand, the predicted probability of attending AET of respondents with tertiary education (ISCED 5) is twice that of those with lower secondary or primary education (ISCED 0-2) in Continental and Southern Europe (from 20% to around 50%).

Figure 5. Conditional probabilities of AET by education levels. Regressions separately run by welfare regimes. Confidence intervals at 95% level of statistical significance.

Finally, significant differences by gender in the participation in job-related AET (ceteris paribus) do not emerge (figure 6), with the exception of a marginally lower probability to take up AET for women in Anglo-Saxon countries.

Figure 6. Conditional probabilities of AET by gender. Regressions separately run by welfare regimes. Confidence intervals at 95% level of statistical significance.

Turning our attention to unmet demand for AET, it is confirmed that workers in jobs at lower risk of automation show slightly higher rates of unmet demand, while the probability of not under-going AET and not expressing demand for it is higher among those most at risk of automation (figure 7). In Continental, Central-Eastern and Anglo-Saxon countries, the increase of no demand category among workers in jobs at high risk of automation is more marked, while the met demand tends to be higher among workers with lowest risk of automation. However, the latter differences are not particularly strong as part of the workers who undertook AET (as shown in figure 1 they are more likely to be employed in low-risk jobs) are still expressing unmet demands.

Figure 7. Conditional probabilities not to have undergone AET and have unmet demand by risk of automation[7]. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.

Women (except in Anglo-Saxon countries) and higher educated workers (with less intensity in CE Europe) are more likely to declare that they failed to take training even though they wanted to (fig.8-9). In all welfare regimes no demand for AET is more present among lower educated workers.

Figure 8. Conditional probabilities not to have undergone AET and have unmet demand by gender. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.

[7] In figure 7-11, the label "no demand" corresponds to those who don't report unmet needs and have not undertaken any AET activities in the previous year; the label "met demand" are those who don't report unmet needs but have participated in AET in the last 12 months; the label "unmet demand" corresponds to demand for AET wanted but not taken in the last 12 months.

Figure 9. Conditional probabilities not to have undergone AET and have unmet demand by education level. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.

The differences between age groups are less intense (figure 10), even if a lower quota of unmet demand is noticeable among older workers (albeit not statistically relevant in Anglo-Saxon countries).

Figure 10. Conditional probabilities not to have undergone AET and have unmet demand by age. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.

No significant differences emerge in terms of the quota of unmet demand between employees and self-employed and between standard and atypical employees (figure 11). However, self-employed and individuals not working are less likely to report any training need at all. This trend is stronger in Central-European and Continental countries.

Figure 11. Conditional probabilities not to have undergone AET and have unmet demand by employment status. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.

5. DISCUSSION

Departing from the meanwhile widely accepted theoretical assumption that participation in adult education is the result of the interplay between individual agency and structural conditions and that individual educational choices are constrained by institutions (Blossfeld et al., 2020; Boeren & Holford, 2016; Desjardins & Rubenson, 2013; Rubenson & Desjardins, 2009) we focused on participation in job-related AET in relation to the risk of job automation by welfare state regime. We aimed to explore variation in this relation across welfare regimes by furthering empirical evidence on demand for and barriers to participation in AET.

Overall, our findings confirm patterns of participation and types of barriers reported in the literature. Even if participation varies widely across countries, a common feature is that it remains unequally distributed. Participation is especially low amongst those most in need: the low-educated, those whose jobs are at high risk of automation as well as non-standard workers. The results of both our descriptive and inferential analysis suggest that the negative relation between risk of automation and probability of participation in AET is robust across welfare regimes (tab 2, fig 2).

Nevertheless, some peculiarities by type of the welfare regime are worth mentioning. In Scandinavian countries, the differential to participate in job-related AET in occupations at low risk of automation vs high risk is lower, while it is highest in Central-Eastern Europe (tab 2). In this outcome and in line with the literature (see section 2.1), the type of welfare state plays a role as Scandinavian countries have measures in place to widen participation in learning opportunities and mitigate inequalities Interestingly, after controlling for individual characteristics, the gap between low and high risk of automation workers in Southern Europe is closer than in other welfare regimes (fig 2).

Workers facing high risk of automation on their jobs report lower rates of unmet demand. This might be related to both individual and structural factors. Low-educated workers are more likely to be found in jobs at high risk of automation; these occupations usually provide fewer workplace training opportunities, which lead to lower awareness of their training needs. Consequently, workers on these jobs experience cumulative disadvantages. The pattern across welfare regimes does not differ in kind, only in degree (fig. 2 -11).

Some countries combine high AET participation with high unmet demand (Scandinavia), others high participation with low unmet demand (Anglo-Saxon countries) and finally others combine low values on both dimensions (Southern and Central-Eastern countries). The latter situation is in line with previous research on demand for and barriers to participation in adult learning. Hovdhaugen and Opheim (2018) show for instance that the demand for AET is substantially higher in countries with high participation rates and that low participation countries do not have a higher proportion of individuals reporting barriers, which prevent them from taking part in AET. The general pattern indicates that in countries with high participation there is a positive learning culture, more opportunities to participate in adult learning and less structural barriers.

Regarding the type of barriers reported across welfare regimes by risk of job automation, the findings are quite interesting. The situational barriers outweigh the institutional ones across all welfare regimes (table 4) with the most balanced ratio in Central-Eastern Europe and most unbalanced in Southern Europe.

The predominance of situational over institutional barriers holds across classes of risk of job automation in all welfare regimes, with respondents in Continental and Central European reporting more evenly balanced constraints. The evidence with regard to perceived barriers to AET participation across welfare regimes is not consistent throughout the literature. By analysing data of the Adult Education Survey, Roosmaa and Saar (2016) found out that all country types display high levels of institutional barriers – particularly the Baltic countries - compared to the Scandinavian countries. Situational barriers were expressed mostly in liberal and continental countries without statistically significant differences between Visegard and Southern European countries (Roosmaa & Saar, 2016, pp. 266–267).

There are some limitations in this study that must be acknowledged.

Countries were clustered in welfare regime types according to the typology by Esping-Andersen and its extensions. Esping-Andersen´s typology has been by far the most influential classification in comparative welfare state research and has been used in various research fields, also with regard to education (Allmendinger & Leibfried, 2003; Willemse & Beer, 2012). Although the typology and its various extensions to other regime types is still widely used, it has been extensively challenged both on empirical and analytical grounds (Danforth, 2014; Ferragina & Seeleib-Kaiser, 2011; Powell, 2015).

Conceptually, the distinction between situational vs. institutional barriers appear to be inconsistent throughout the literature. The same is true for the operationalisation of the categories. Cross (1981), who developed the classification of barriers to AET participation, points to this issue as well as Hovdhaugen and Opheim (2018) and Roosmaa and Saar (2016).

Methodologically, the model's explanatory power is low when analysing the unmet demand (pseudo R2: 9.7%) suggesting the presence of some unobserved patterns.

6. CONCLUSIONS

Previous research (OECD, 2019) has established that workers whose jobs are at high risk of automation are significantly less likely to engage in adult education and training than those in less exposed jobs. Our contribution aimed to explore participation patterns by risk of job automation across welfare regimes; this might allow a better understanding of the institutional factors promoting and equalizing access to AET.

Our findings suggest that while obviously some welfare regimes are better than others at getting workers to participate in job-related AET, workers in occupations at high-risk of automation were found to be consistently less likely to do so (accounting for gender, age, education, employment status), quite irrespective of welfare regime. Although age, educational attainment, and work-related factors such as employment status are linked to inequality in participation in all countries, the level of inequality varies substantially between countries and welfare regimes.

Low educated and low skilled workers are likely to bear the brunt of the adjustment costs to technological changes as their jobs are facing a higher risk of automation compared to highly qualified workers. Nevertheless, those workers most in need of training and re-skilling are least likely to get some. Institutional, situational and dispositional barriers create a vicious circle of limited resources due to social origins, bad jobs, and insufficient training and learning opportunities, in which low-skilled and low-qualified people tend to be deadlocked in.

The use and extent of education and social policy instruments such as active labour market measures emphasising upskilling and reskilling, public spending in open and flexible education and training systems, establishment of skills recognition system and programmes targeting the most vulnerable groups can be crucial to foster training opportunities for workers in occupations at high-risk of automation. Evidence on cross-national patterns of organized adult learning supports this claim by pointing out several specific institutional features that enable the provision and take up of AET and thus, can play a role in fostering high and widely distributed levels of participation in AET (Desjardins & Ioannidou, 2020).

No less important is the use of public policies and stakeholder arrangements to influence the skill orientation of the economy by emphasising high skills, high wages, and innovative and high quality products (Crouch & Streeck, 1997; Regini & Esping-Andersen, 2000) compared to low-value-added goods and services for local or domestic markets, based upon labour-intensive and low-skill production system. Several studies demonstrate a strong link between the skill orientation of the economy and the extent and distribution of adult learning opportunities (Desjardins, 2017; Green, 2006).

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Table 1. Risk of automation by welfare regime

	Scandinavian	Southern	Continental	Central-Eastern	Anglo-Saxon
Mean risk of automation	42.1%	50.0%	49.6%	49.7%	42.2%
Share of jobs in occupations at:					
High risk of automation	19.0%	51.7%	51.2%	49.8%	33.6%
Low risk of automation	81.0%	48.3%	48.8%	50.2%	66.4%

High (low) risk defined as probability of automation over (under) 50%.

Table 2. Participation in job-related AET by risk of automation.

	Scandinavian	Southern	Continental	Central-Eastern	Anglo-Saxon
Participation rate	55.2%	29.5%	42.2%	34.0%	49.9%
Participation rate in job-related AET in occupations at:					
High risk of automation	39.2%	21.3%	30.9%	22.5%	35.6%

Low risk of automation	59%	38.2%	54.0%	45.4%	57.2%
Low to high ratio	1.51	1.79	1.75	2.02	1.61

High (low) risk defined as probability of automation over (under) 50%.

Table 3. Unmet demand for AET by risk of automation.

	Scandinavian	Southern	Continental	Central-Eastern	Anglo-Saxon
No AET participation and no demand expressed	35.4	59.6	49.4	62.1	42.1
AET participation and no demand expressed	37.0	19.3	26.8	26.6	36.1
Unmet demand	27.6	21.1	23.8	11.3	21.8
High risk of automation					
No AET participation and no demand expressed	48.5	68.2	60.8	73.9	55.6
AET participation and no demand expressed	30.0	15.2	21.3	19.2	26.7
Unmet demand	21.6	16.6	18.0	7.0	17.7
Low risk of automation					
No AET participation and no demand expressed	32.4	50.4	37.4	50.4	35.3
AET participation and no demand expressed	38.6	23.7	32.6	34.0	40.8
Unmet demand	29.0	25.9	30.0	15.7	23.9
Low to high ratio					

No AET participation and no demand expressed	0.67	0.74	0.62	0.68	0.63
AET participation and no demand expressed	1.29	1.56	1.53	1.77	1.53
Unmet demand	1.34	1.56	1.67	2.24	1.35

High (low) risk defined as probability of automation over (under) 50%.

Table 4. Barriers to AET participation by risk of automation.

	Scandinavian	Southern	Continental	Central-Eastern	Anglo-Saxon
Ratio of situational vs institutional barriers to participation in AET in occupations at:					
High risk of automation	1.35	2.96	2.14	1.17	2.36
Low risk of automation	2.79	3.67	2.73	1.66	1.67
Low-to-high ratio	2.07	1.24	1.28	1.42	0.71

High (low) risk defined as probability of automation over (under) 50%.

Figure 1. Conditional probabilities estimated from logistic regression on probability of AET. Confidence intervals at 95% level of statistical significance.

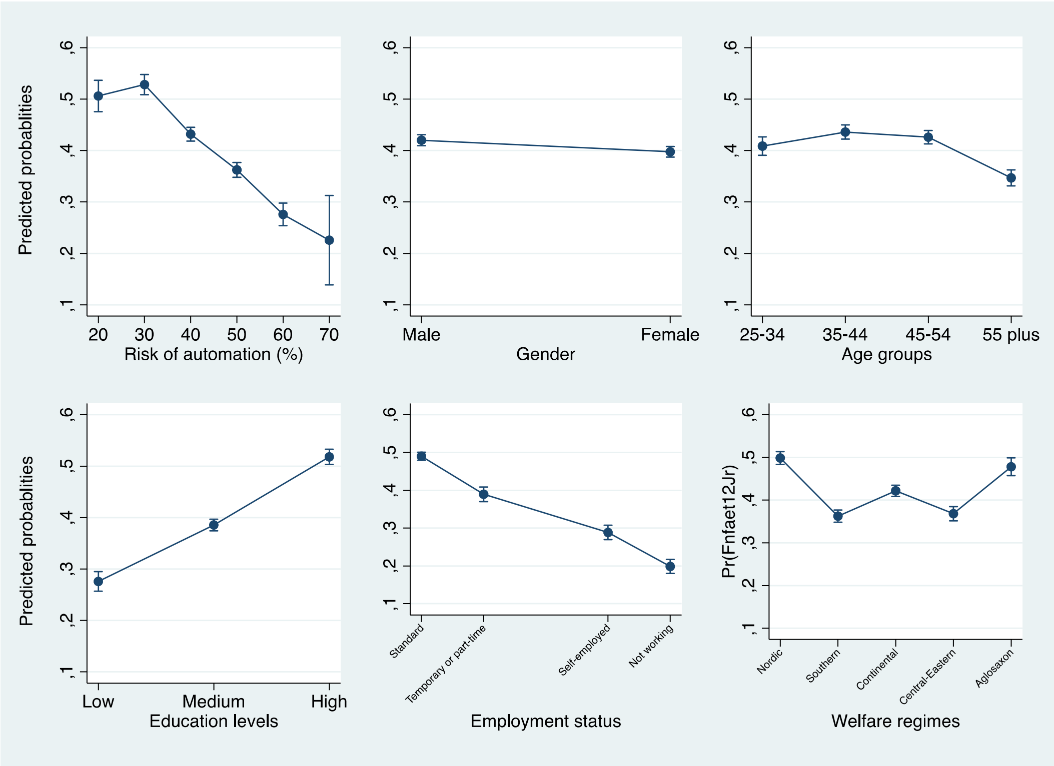
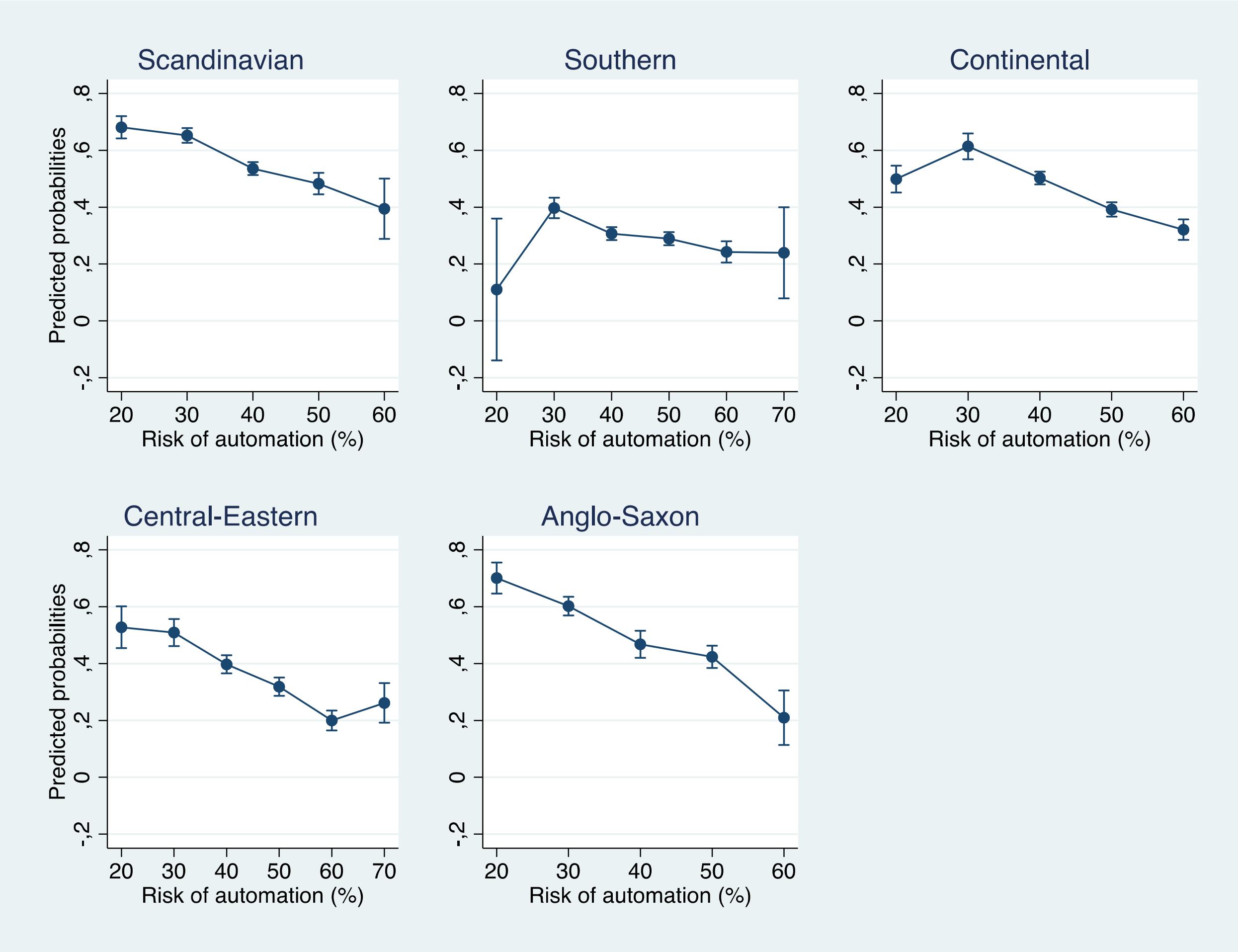


Figure 2. Conditional probabilities of AET by risk of automation. Regressions separately run by welfare regimes. Confidence intervals at 95% level of statistical significance.


Scandinavian
Southern
Continental
Central-Eastern
Anglo-Saxon
Predicted probabilities
Risk of automation (%)
-,2
0
,2
,4
,6
,8
20
30
40
50
60
70

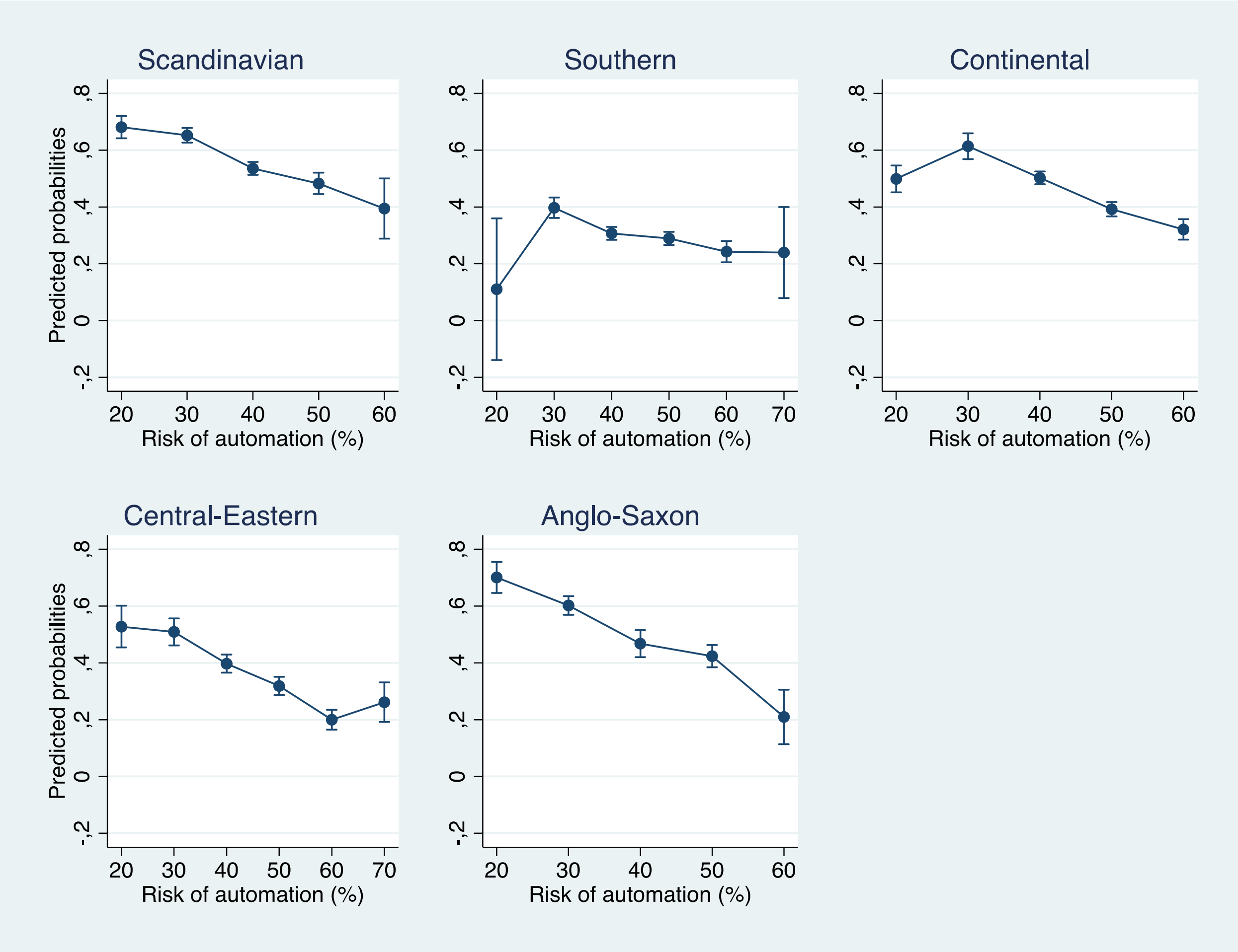

Scandinavian
Southern
Continental
Central-Eastern
Anglo-Saxon
Predicted probabilities
Risk of automation (%)
-,2
0
,2
,4
,6
,8
20
30
40
50
60
70

Figure 3. Conditional probabilities of AET by age. Regressions separately run by welfare regimes.

Confidence intervals at 95% level of statistical significance.

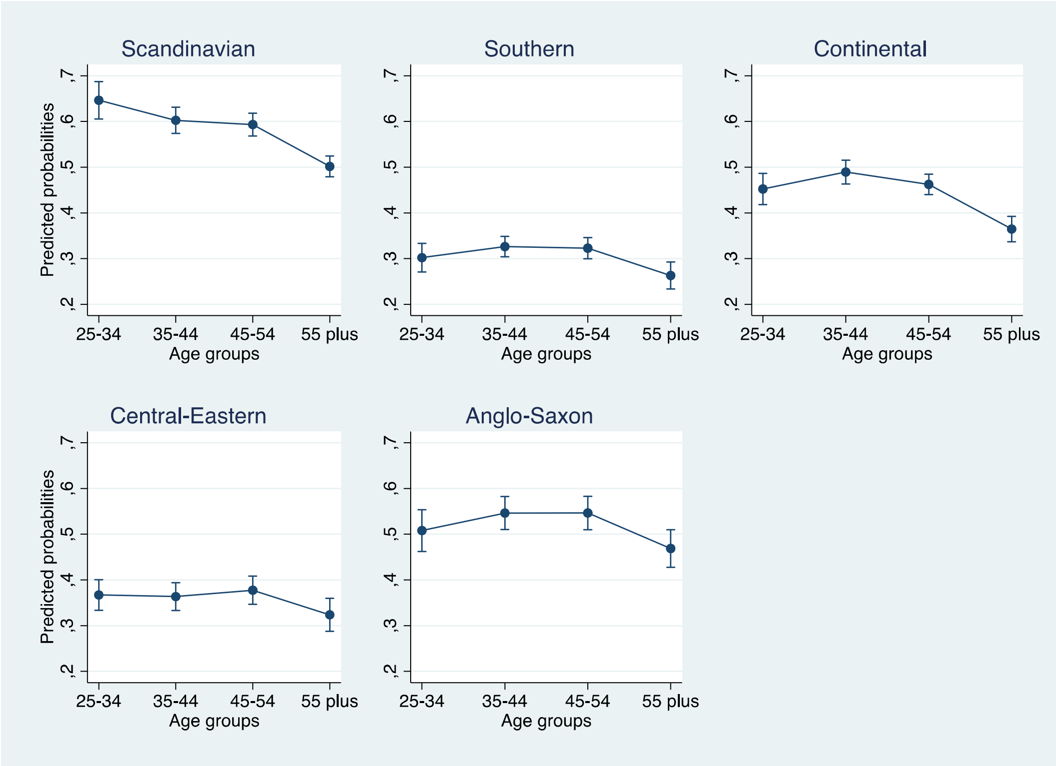


Figure 4. Conditional probabilities of AET by employment status. Regressions separately run by welfare regimes. Confidence intervals at 95% level of statistical significance.

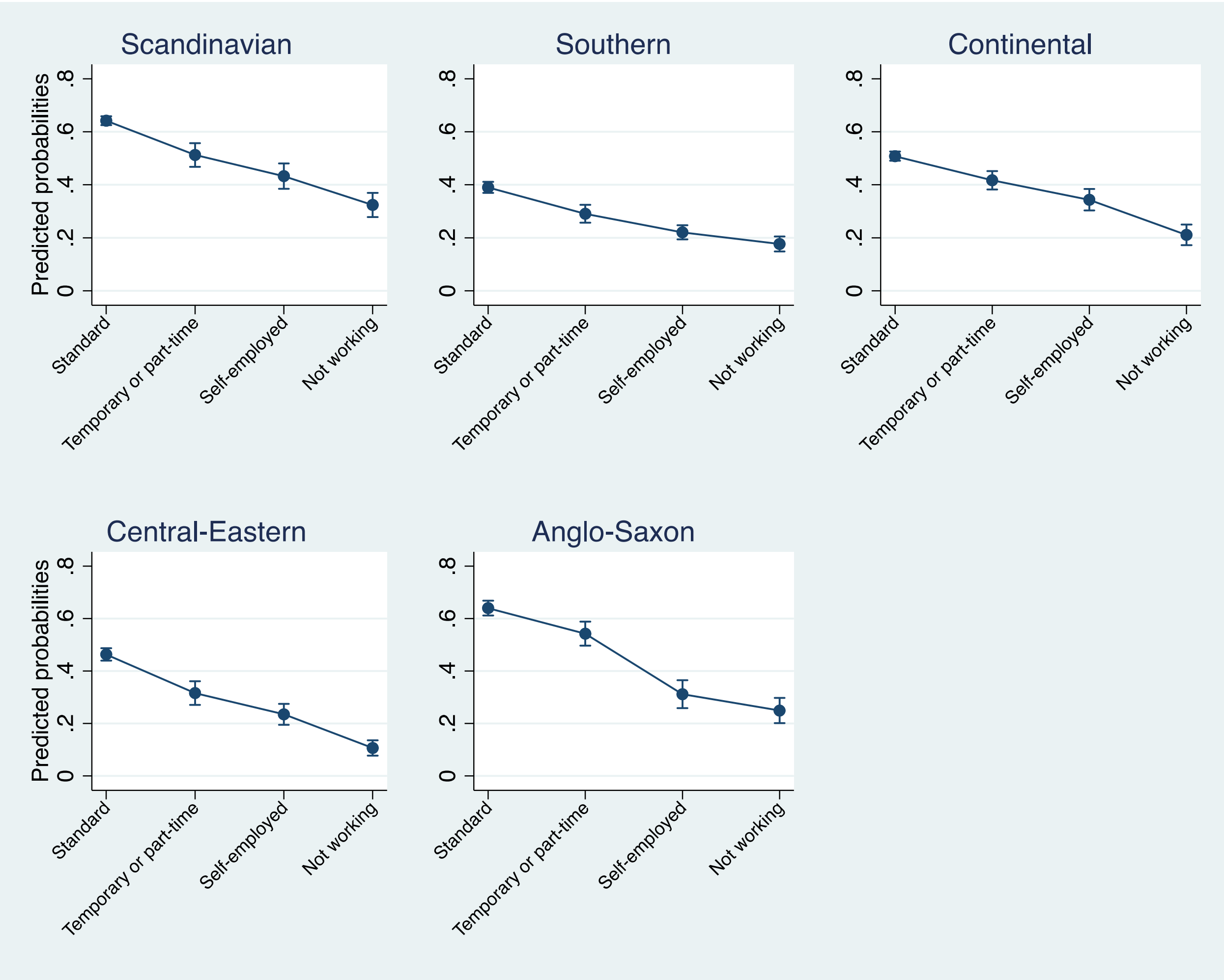


Figure 5. Conditional probabilities of AET by education levels. Regressions separately run by welfare regimes. Confidence intervals at 95% level of statistical significance.

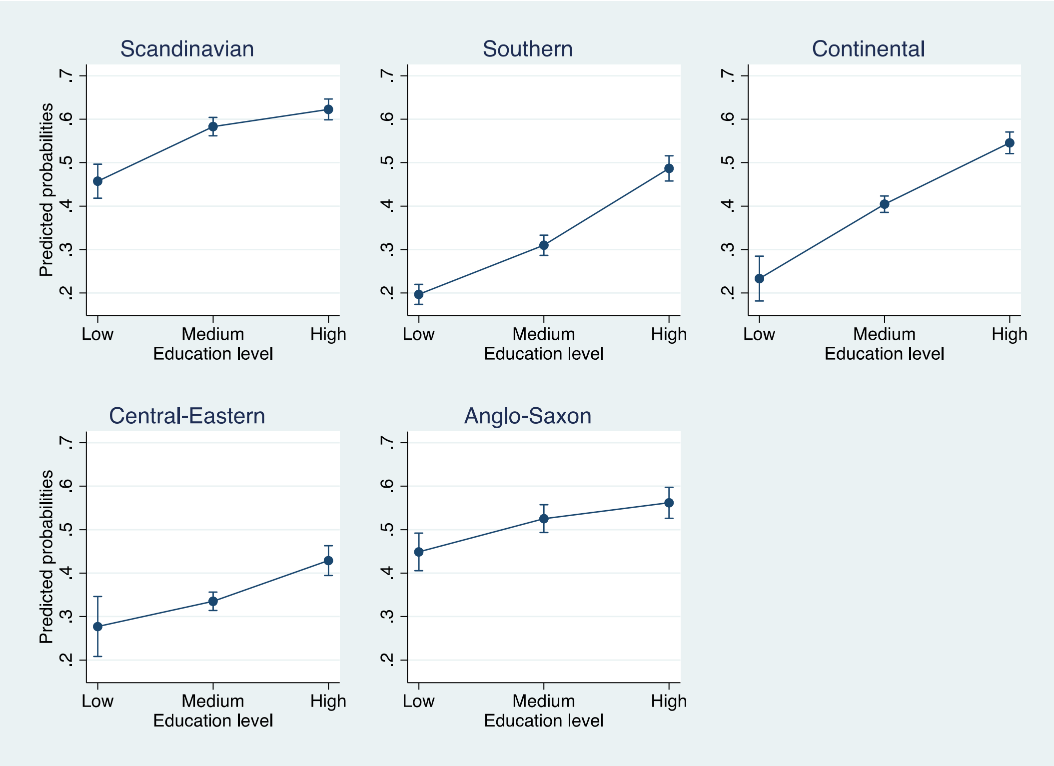


Figure 6. Conditional probabilities of AET by gender. Regressions separately run by welfare regimes.

Confidence intervals at 95% level of statistical significance.

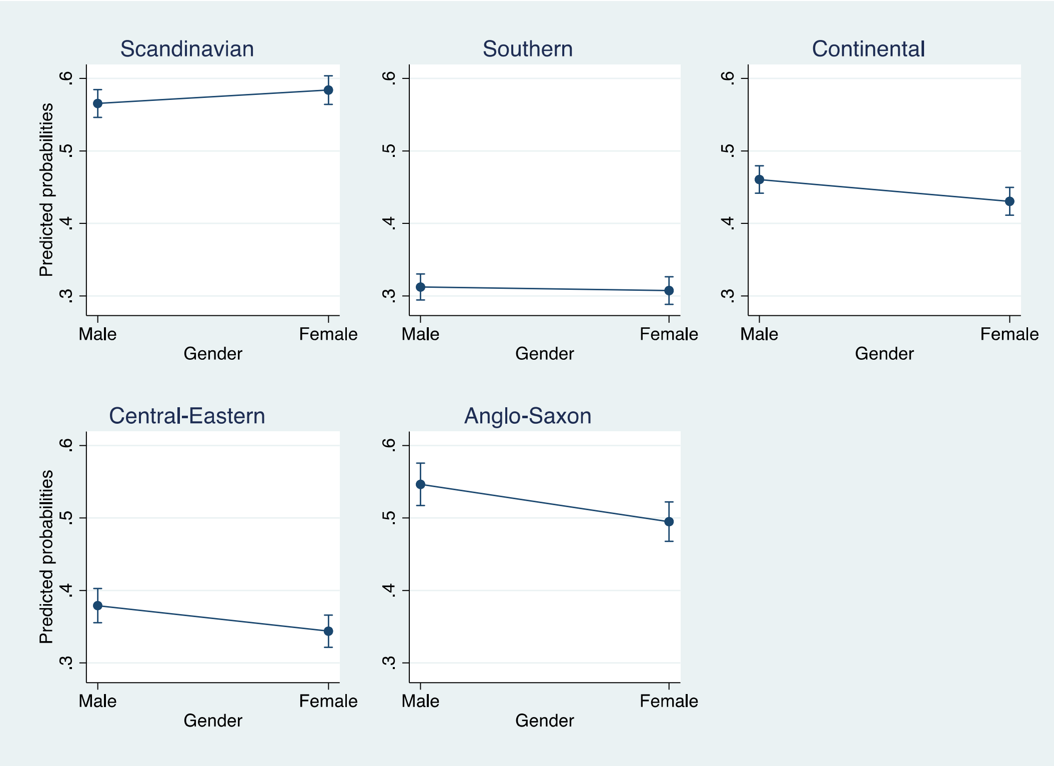
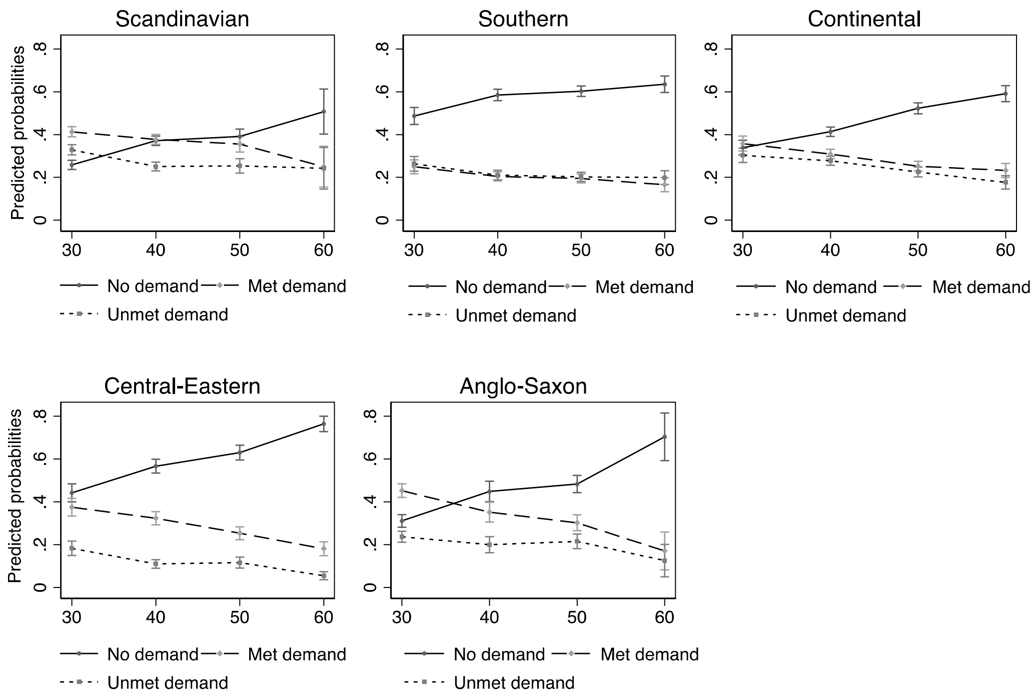


Figure 7. Conditional probabilities not to have undergone AET and have unmet demand by risk of automation[1]. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.



[1] In figure 7-11, the label "no demand" corresponds to those who don't report unmet needs and have not undertaken any AET activities in the previous year; the label "met demand" are those who don't report unmet needs but have participated in AET in the last 12 months; the label "unmet demand" corresponds to demand for AET wanted but not taken in the last 12 months.

Figure 8. Conditional probabilities not to have undergone AET and have unmet demand by gender.

Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.

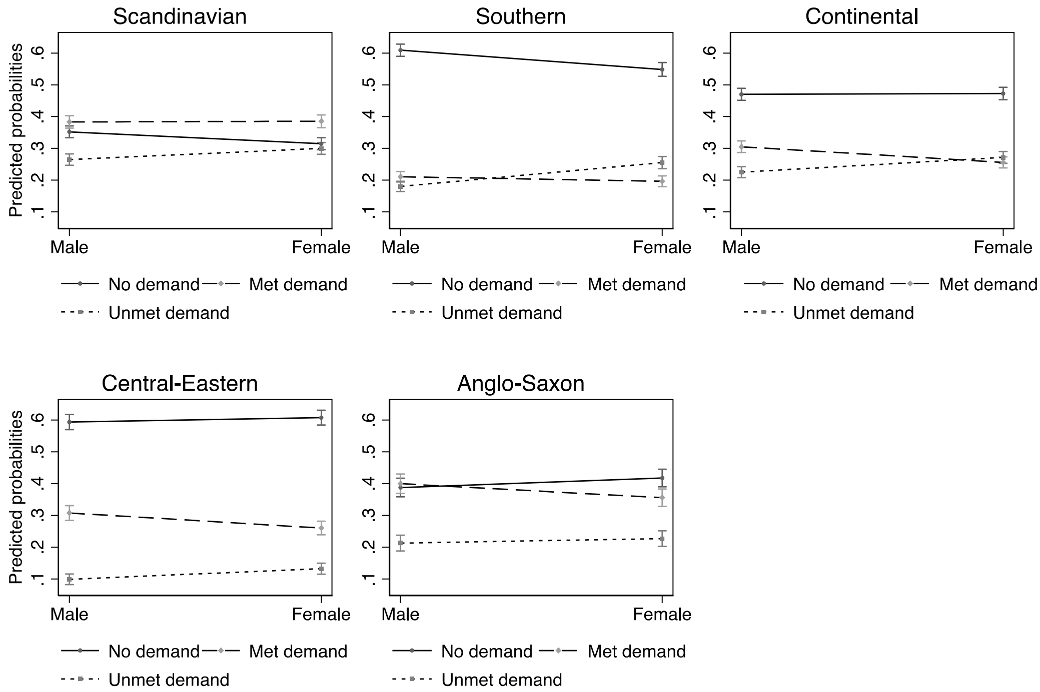


Figure 9. Conditional probabilities not to have undergone AET and have unmet demand by education level. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.

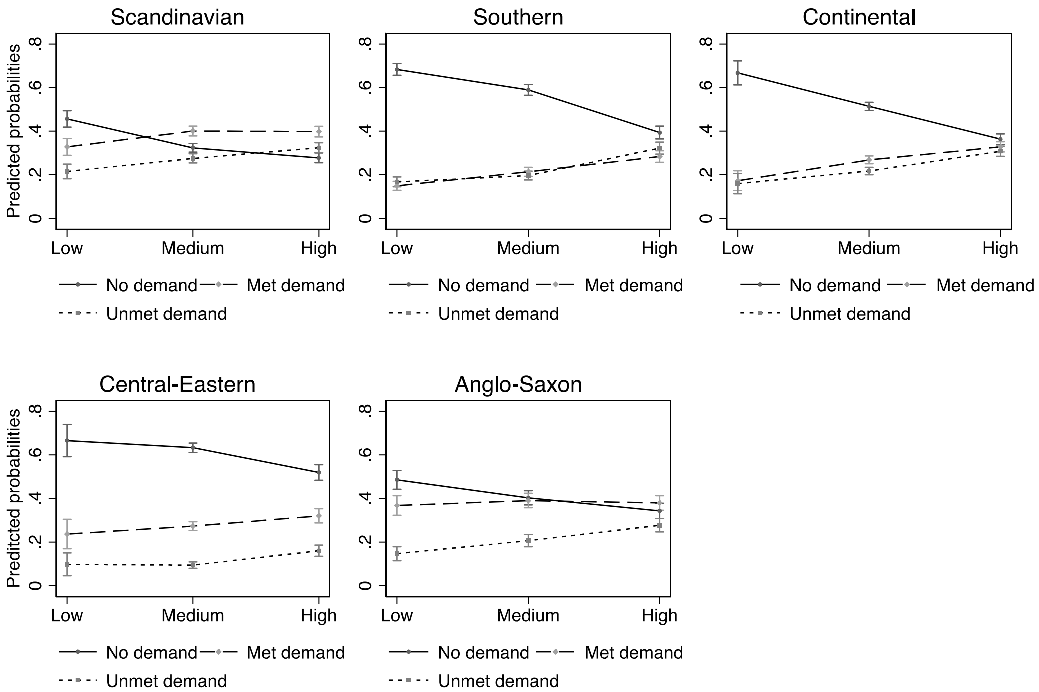


Figure 10. Conditional probabilities not to have undergone AET and have unmet demand by age. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.

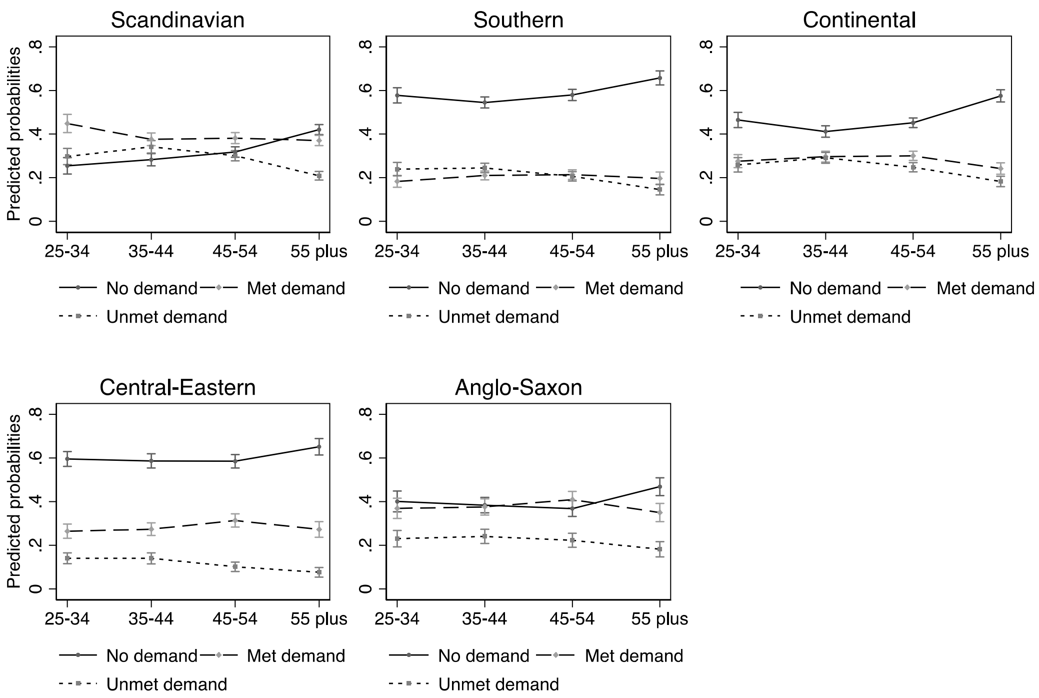
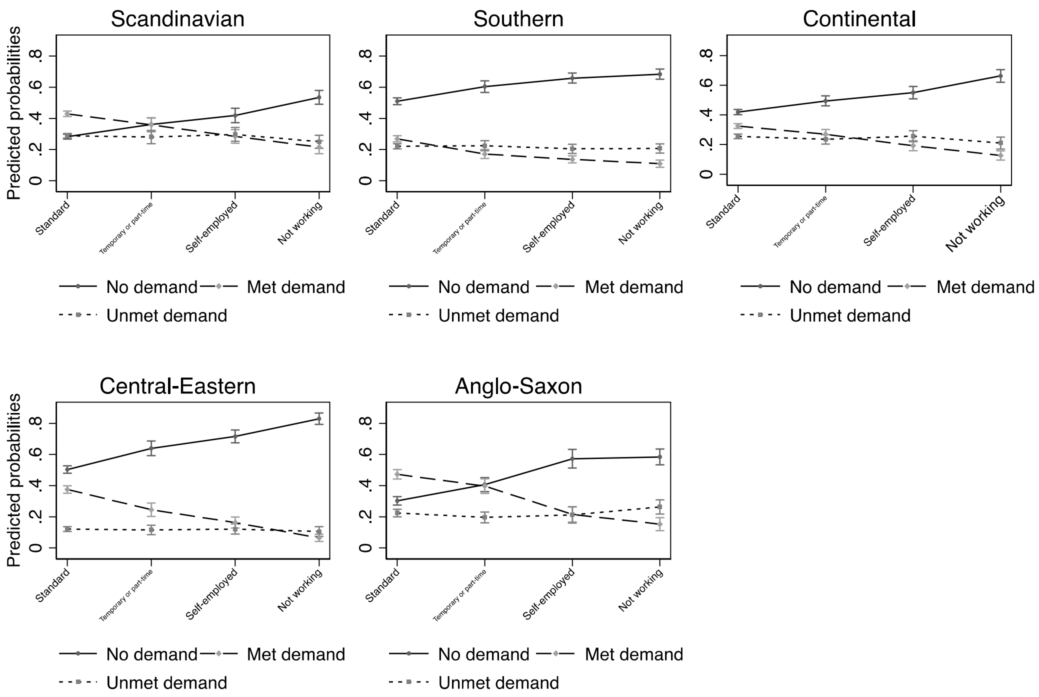


Figure 11. Conditional probabilities not to have undergone AET and have unmet demand by employment status. Estimated from multinomial logistic regression. Confidence intervals at 95% level of statistical significance.



ONLINE APPENDIX

Table I: Overview of databases, keywords combinations and results

Database	Combination of keywords			Number of results
ERIC	"risk of job automation"	AND	"participation in training"	0
	"risk of job automation"	/	"participation in training"	0
	"risk of job automation"	AND	"training"	0
	"risk of job automation"	AND	training	0
	(risk of job automation)	AND	training	0
	risk of job automation	AND	training	6 (2 from 2001 onwards)
	risk of job automation	AND	participation in training	34 (3 from 2001 onwards)
	risk of job automation	AND	adult learning	24 (8 from 2001 onwards; 7 further considered because of a duplication)
	risk of job automation	AND	further education	25 (10 from 2001 onwards)
	risk of job automation	AND	further education and training	0
	risk of job automation	AND	continuing education and training	0
	risk of job automation	AND	continuing education	20 (4 from 2001 onwards)

	risk of job automation	AND	re skilling	1
	risk of job automation	AND	reskilling	0
	risk of job automation	AND	re-skilling	0
Fachportal Pädagogik	"risk of job automation"	AND	training	0
	risk of job automation	AND	training	7 (4 from 2001 onwards)
	risk of job automation	AND	participation in training	0
	risk of „job automation"	AND	participation in training	0
	risk of job automation	AND	„participation in training"	0
	risk of job automation	AND	„adult learning"	0
	risk of job automation	AND	adult learning	1
	risk of job automation	AND	further education	1
	risk of job automation	AND	further education and training	0
	risk of job automation	AND	continuing education	0
	risk of job automation	AND	continuing education and training	0
	risk of job automation	AND	„re skilling"	0
	risk of job automation	AND	re skilling	0
	risk of job automation	AND	reskilling	0

Springer Link	risk of „job automation“	AND	„adult learning“	1
	risk of “job automation”	AND	“adult education”	4 (2 from 2001 onwards)
	risk of “job automation”	AND	„further education“	3
	risk of “job automation”	AND	„further education and training“	1
	risk of “job automation”	AND	„further education“ and training	3 (identical with „further education”)
	risk of “job automation”	AND	„continuing education and training“	1 (from 1985)
	risk of “job automation”	AND	„continuing education“ and training	2 (1 from 2001 onwards)
	risk of “job automation”	AND	„re skilling“	0
Sage Journals (all journals)	“risk of job automation”	AND	training	0
	“risk of job automation”	AND	re*skilling	0
	“risk of job automation”	AND	re skilling	0
	risk of “job automation”	AND	re*skilling	1
	risk of „job automation“	AND	training	8 (5 from 2001 onwards)
	risk of “job automation”	AND	„adult learning“	0
	risk of “job automation”	AND	„further education“	0
	risk of “job automation”	AND	further education	0

	risk of “job automation”	AND	„continuing education“	0
	risk of “job automation”	AND	continuing education	4 (2 from 2001 onwards)
	risk of “job automation”	AND	adult learning	4 (2 from 2001 onwards; identical with continuing education)
Sage Journals (Adult and Continuing Education; Adult Education Quarterly; Adult Learning)	risk of job automation	AND	training	11 (7 from 2001 onwards)
	risk of job automation	AND	reskilling	0
	risk of job automation	AND	re*skilling	0
	risk of “job automation”	/	/	0
Google Scholar	“risk of job automation”	AND	training	50 (46 from 2001 onwards; after content-related differentiation 18 further considered)
	“risk of job automation”	AND	reskilling	12 (after content-related differentiation 3 further considered)
	“risk of job automation”	AND	“adult learning”	5 (after content-related differentiation 4 further considered)
	“risk of job automaton”	AND	“further education“	7 (after content-related

				differentiation 4 further considered)
	“risk of job automaton”	AND	“continuing education“	2 (after content-related differentiation 1 further considered)
Researchgate	“risk of job automation“	AND	training	1
	“risk of job automation”	AND	reskilling	0
	“risk of job automation”	AND	“adult learning”	0
	“risk of job automation”	AND	“further education”	5
	“risk of job automation”	AND	“continuing education”	0
BIBB	“risk of job automation”	AND	training	0
	risk of job automation (= Suchgruppe)	AND	training	9 (one doubling, 8 further considered)
	risk of job automation (= Suchgruppe)	AND	reskilling	0
	risk of job automation (= Suchgruppe)	AND	re*skilling	4 (one doubling, 3 further considered)
	risk of job automation (= Suchgruppe)	AND	adult learning	7 (identical with former BIBB searches)
	risk of job automation (= Suchgruppe)	AND	further education	7 (identical with former BIBB searches)

	risk of job automation (= Suchgruppe)	AND	continuing education	7 (identical with former BIBB searches)
ECONBIZ	“risk of job automation”	AND	training	0
	risk of “job automation”	AND	training	0
	“job automation”	AND	training	0
	“risk of automation”			27
	“risk of automation”	AND	training	8 (doublings, 2 further considered)
	“risk of automation”	AND	adult learning	1
	“risk of automation”	AND	further education	0
	“risk of automation”	AND	continuing education	0
	“risk of automation”	AND	re*skilling	0
	“risk of automation”	AND	reskilling	0
	“risk of automation”	AND	reskill*ing	0
	„risk of automation“	AND	training	0
GESIS	„job automation“	AND	training	4
	„job automation“	AND	reskilling	0
	„job automation“	AND	re*skilling	0
	„job automation“	AND	„adult learning“	0
	„job automation“	AND	„further education“	0

	„job automation“	AND	„continuing education“	0
	„job automation“	AND	education	2
	„risk of job automation“	AND	training	16 (12 further considered)
	„risk of job automation“	AND	„adult learning“	22 (9 further considered)
OECD Library	„risk of job automation“	AND	„further education“	18 (6 further considered, identical with „adult learning”)
	„risk of job automation“	AND	“continuing education”	7 (3 further considered; identical with former searches)
	„risk of job automation“	AND	reskilling	21 (6 further considered)
	„risk of job automation“	AND	training	25 (without doublings and in English 7 further considered)
	„risk of job automation“	AND	“adult learning”	0
BASE	„risk of job automation“	AND	“further education”	0
	„risk of job automation“	AND	“continuing education”	0
	„risk of job automation“	AND	reskilling	0
	„risk of job automation“	AND	re*skilling	0

„risk of job automation“	29 (11 further considered)
In total: 485 hits ⇨ after a content-based differentiation and the exclusion of duplications ⇨ 104 publications were considered in the initial review (tab. 2)	

Table II: Publications reviewed in-depth

1.	Arntz, M.; Gregory, T. & Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis. *OECD Social, Employment and Migration Working Papers*, No. 189, OECD Publishing, Paris. http://dx.doi.org/10.1787/5jlz9h56dvq7-en
2.	Arntz, M.; Gregory, T. & Zierahn, U. (2019). Digitization and the Future of Work: Macroeconomic Consequences. In: Institute for Labour Economics (Ed.), *Discussion Paper Series*, No. 12428, Bonn. http://ftp.iza.org/dp12428.pdf
3.	Bentaouet Kattan, R.; Macdonald, K. A. D. & Patrinos, H. A. (2018). Automation and labor market outcomes: the pivotal role of high-quality education. In: World Bank Group (Ed.), *Policy Research working paper*, No. WPS 8474, Washington, D.C. http://documents.worldbank.org/curated/en/356581528983322638/Automation-and-labor-market-outcomes-the-pivotal-role-of-high-quality-education
4.	Carey, D. (2017). Adapting to the changing labour market in New Zealand, *OECD Economics Department Working Papers*, No. 1420, OECD Publishing, Paris. https://doi.org/10.1787/e6ced642-en
5.	Cummins, P. A.; Yamashita, T.; Millar, R. J. & Sahoo, S. (2019). Problem-Solving Skills of the U.S. Workforce and Preparedness for Job Automation. *Adult Learning*, *30*(3), 111–120. https://doi.org/10.1177/1045159518818407
6.	Doménech, R.; García, J. R.; Montañez, M. & Neut, A. (2018). How vulnerable is Spanish employment to the digital revolution? In: BBVA (Ed.). *Working Paper*. https://www.bbvaresearch.com/wp-content/uploads/2018/03/How-vulnerable-is-Spanish-employment-to-the-digital-revolution.pdf

7.	European Union (2019). The changing nature of work and skills in the digital age. Publications Office of the European Union, Luxembourg. https://op.europa.eu/en/publication-detail/-/publication/508a476f-de75-11e9-9c4e-01aa75ed71a1
8.	Filippi, E. & Trento, S. (2019). The probability of automation of occupations in Italy. In: L. Andreozzi & M. Tecilla (Ed.), DEM Working Papers, No. 2019/17, Trento. https://pdfs.semanticscholar.org/b617/fd8836f61638d2119533a3add99b10834f6f.pdf
9.	Flores, S.; Canare, T.; Francisco, J. P. & Caboverde, C. (2018). Mapping the 4IR At-Risk Workers in the Philippines. *SSRN Electronic Journal.* 10.2139/ssrn.3298550. https://www.researchgate.net/publication/329584663_Mapping_the_4IR_At-Risk_Workers_in_the_Philippines
10.	Lee, S.; Ostermeier, M.; Keese, M.; Dølvik, J. E.; Lemne, C.; Kvam, B.; Wallin, G.; Preisler, M.; Sigurðardóttir, G. H.; Floman, M.; Lindahl, B. & Ahlberg, K. (2019). *The future labour market in the Nordic countries– the impact of technological development on jobs and the need for competence.* Nordic Council of Ministers/Publication Unit, Copenhagen. http://norden.divaortal.org/smash/get/diva2:1358726/FULLTEXT01.pdf
11.	Malo, M. & Begoña, C. (2019): Do old and new labour market risks overlap? Automation, offshorability, and non-standard employment. In: MPRA (Ed.). *MPRA Paper*, No. 95058. https://mpra.ub.uni-muenchen.de/95058/
12.	Michlits, D.; Mahlberg, B. & Haiss, P. R. (2019). Industry 4.0 – The Future of Austrian Jobs. http://dx.doi.org/10.2139/ssrn.3461525
13.	Nedelkoska, L. & G. Quintini (2018). Automation, skills use and training, In: OECD (Ed.). *OECD Social, Employment and Migration Working Papers*, No. 202, OECD Publishing, Paris. http://dx.doi.org/10.1787/2e2f4eea-en
14.	OECD (2019). *Getting Skills Right: Future-Ready Adult Learning Systems.* OECD Publishing, Paris. https://doi.org/10.1787/9789264311756-en

15.	OECD (2019). *OECD Employment Outlook 2019: The Future of Work.* OECD Publishing, Paris. https://doi.org/10.1787/9ee00155-en
16.	OECD (2019). *Skills Matter: Additional Results from the Survey of Adult Skills,* OECD Skills Studies. OECD Publishing, Paris. https://doi.org/10.1787/1f029d8f-en
17.	OECD (2020). Fostering greater participation in adult learning. In: OECD (Ed.), *OECD Skills Strategy Slovak Republic: Assessment and Recommendations.* OECD Publishing, Paris. https://doi.org/10.1787/bb47eb91-en
18.	OECD (2020). Technological diffusion and managing the associated economic transitions. In: OECD (ed.), *OECD Economic Surveys: Ireland 2020.* OECD Publishing, Paris. https://doi.org/10.1787/8e5bcb27-en
19.	Pouliakas, K. (2018). Determinants of automation risk in the EU labour market. A skills-needs approach. In: Institute for Labour Economics (Ed.), *Discussion Paper Series*, No. 11829, Bonn. http://ftp.iza.org/dp12428.pdf
20.	Rainie, L. & Anderson, J. (2017*). The Future of Jobs and Jobs Training*. Pew Research Center. http://www.pewinternet.org/2017/05/03/the-future-of-jobs-and-jobs-training/
21.	Schmidpeter, B. & Winter-Ebmer, R. (2019). Automation, offshoring and the role of public policies. In: Department of Economics, Johannes Kepler University Linz, Austria (Ed.), *Economics Working Paper*, 2019-04. https://ideas.repec.org/p/jku/econwp/2019_14.html
22.	Siekmann, G. & Fowler, C. (2017). Identifying Work Skills: International Approaches. In: National Centre for Vocational Education Research (Ed.), *NCVER Discussion Paper*, Adelaine. https://www.ncver.edu.au/__data/assets/pdf_file/0028/1456660/Identifying-work-skills-report.pdf

23.	Sorgner, A. (2017). The automation of jobs: a threat for employment or a source of new entrepreneurial opportunities? *Foresight and STI governance*, 11 (3), 37-48. https://ideas.repec.org/a/hig/fsight/v11y2017i3p37-48.html
24.	Ure, O. B., & Skauge, T. (2019). Skills and employment under automation: active adaptation at the local level. *International Journal for Research in Vocational Education and Training*, 6 (3), 203-223. https://doi.org/10.13152/IJRVET.6.3.1
25.	Van Kleunen, A.; Bashay, M.; Overton, S. & Contractor, H. (2019). An Unequal Future of Work Requires Different Training Strategies for Vulnerable Workers. In: The Hatcher Group (Ed.). *Taking Action: Positioning Low-Income Workers to Succeed in a Changing Economy,* 16-22. https://m.nationalskillscoalition.org/federal-policy/body/Positioning-low-income-workers-to-succeed-in-a-changing-economy.pdf